

Artificial intelligence in simulation

Tuncer I. Ören

*Ottawa Center of the McLeod Institute of Simulation Sciences,
Computer Science Department, University of Ottawa,
Ottawa, Ontario, Canada K1N 6N5
E-mail: oren@csi.uottawa.ca*

The aims are to clarify some basic concepts on cognizant simulation as well as on the similarity and the relationships of AI and simulation; provide an inventory and a taxonomy of AI-based (cognizant) simulation and AI-assisted simulation (cognizant simulation environments); and to indicate some desirable research directions.

Keywords: AI-based simulation, AI-assisted simulation, cognizant simulation, cognizant simulation environments, taxonomy of cognizant simulation, taxonomy of cognizant simulation environments.

1. Introduction

Simulation has a good tradition of contributing to the advancement of disciplines in engineering, exact sciences and in the humanities. With the application of artificial intelligence (AI) in simulation, we are experiencing the advent of another type of simulation. The emerging field is called cognizant, intelligent, expert, rule-based, or knowledge-based simulation. It may be beneficial to assess the achievements and the developments (or lack of it) of cognizant simulation to steer it for a better future. Some overviews of AI in simulation are given by Bradley [24], Elzas et al. [55], Gaines [77], Hopple [95], Kerckhoffs et al. [112], Lehman [129], O'Keefe et al. [156], Round [184], Shannon [198], Synder and Mackulack [212], and Tsatsoulis [219].

In this article, some basic concepts are clarified, an inventory and a taxonomy of the applications of artificial intelligence in simulation are given. Some desirable research directions are also discussed. The inventory of the existing systems is presented by application areas and by the type of the environments. The taxonomy is developed for cognizant simulation and for cognizant simulation environments. Taxonomy of cognizant simulation includes simulation with nested neural nets, knowledge-based simulation, qualitative simulation, multiparadigm simulation, simulation with a nested knowledge-based system, and knowledge-based systems with a nested simulation system. Taxonomy of cognizant simulation environments includes cognizant interfaces, cognizant environments for single and multiparadigm simulation (for models, model parameters, experiments, programs, quality assurance,

and AI components), cognizant environments with a nested knowledge-based system, and comprehensive cognizant environments. In addition to the research possibilities which exist in each category of cognizant simulation and cognizant simulation environments, desirable research directions are discussed in the following areas: knowledge bases for cognizant simulation, reliability issues in cognizant simulation, advanced query systems for cognizant simulation, machine learning through simulation, intelligent training simulators, and repository based cognizant simulation environments.

1.1. SIMULATION

Simulation can be considered from technical, knowledge representation and processing, and pragmatic points of view. Having the right perception of simulation would help us to explore its potentials fully and to explore its synergies with related scientific fields including AI.

From the technical point of view, simulation is experimentation with dynamic models. Simulation has a multitude of types, offers experimentation with a very large number of types of dynamic models including morphogenetic, adaptive, learning and goal-directed models, and deals with several types of model behavior such as discrete, continuous, piece-wise continuous, and mixed behavior.

From a knowledge representation and processing point of view, simulation is a model based experiential knowledge generation activity. Synergies of simulation can be defined with several types of nonexperiential knowledge generation techniques such as optimization, statistical and logical inferencing; as well as symbolic processing of models, and other types of knowledge processing such as machine learning where knowledge to be scrutinized for learning purposes can be generated under well defined experimental conditions.

From a pragmatic point of view, for any analysis and control problem, if the real system is not available or not accessible for experimentation or if the experimentation cannot be conveniently carried out on the real system, simulation offers the only logical choice to perform experimentations. In pilot training for example, even when aircrafts are available, both pilots and the airline companies would definitely prefer aircraft simulators rather than the aircrafts themselves. For any type of design problem, simulation makes experimentation possible even before the realization of the real system, which eliminates the necessity of prototypes. In fact, in simulation, one can observe the behavior of a model under well defined conditions which might include abnormal ones. Of course, the necessity of validating the model used in simulation ties the abstract aspect of simulation with reality.

1.2. AI AND KNOWLEDGE-BASED SYSTEMS

Intelligence (human, animal, or machine) is an adaptive and goal-directed knowledge processing ability. The term artificial intelligence was coined by John

McCarthy in 1956. The subject matter of artificial (or machine) intelligence covers several types of cognitive processes. Two different views form the roots of AI: understanding human intelligence and building machines that surpass human intelligence.

In order to understand human intelligence, Newell and Simon [152] were the early scientists interested in the simulation of human thought processes (cognitive abilities). Simon also states a fundamental role of simulation: "The real power of the simulation technique is that it provides not only a means for stating a theory but also a very sharp criterion for testing whether the statement is adequate." [152, p. 123].

The opposite view was to build super intelligent computers having cognitive abilities far superior than the humans. Davis and Hersh who quoted from Good [85] state that "first of all that there is no point in building a machine with the intelligence of a man, 'since it is easier to construct human brains by the usual method.' One should therefore build an ultra-intelligent machine which may 'be defined as a machine that can far surpass all the intellectual activities of any man however clever'" [41, p. 256]. This dichotomy in AI still continues. See for example, "Two Approaches to Machine Intelligence" edited by Williams [230].

The field of knowledge-based systems is a branch of AI. "Three fundamental concepts of knowledge-based systems distinguish them from conventional algorithmic programs and from general search-based programs: (1) The separation of the knowledge from how it is used. (2) The use of highly specific domain knowledge. (3) The heuristic rather than algorithmic nature of the knowledge employed." [84, p. 22]. Most commonly used knowledge-based systems are rule-based systems.

1.3. THE SIMILARITY AND RELATIONSHIPS OF AI AND SIMULATION

Some researchers consider "searching" as the essence of AI. This is due to the inferencing mechanism working on a set of rules and facts. Given a goal and some facts which constitute the initial condition for the inferencing, the search is done in two ways. In forward chaining, the inferencing mechanism starts with the initial conditions and checks the rules for which the conditions are satisfied. Then the action parts are activated to create new facts. The process continues until the goal is reached, or until an impossibility to make any progress is established. In backward chaining, the mechanism starts with the goal and determines which rule(s) need(s) to be activated to satisfy it.

A simulation study consists of a set of simulation experiments (simulation runs) where model behavior is generated. Before and after every simulation run, prerun and postrun activities exist. Similarly, before and after of a simulation study, other activities, called prestudy and poststudy activities exist. Prestudy activities can include an experimentation shell to design and monitor simulation runs. Poststudy activities can include comparison of the results of each simulation run (via the values of the performance index computed as postrun activities).

Shannon and Centeno rightly pointed out the following:

“Finally, the progress being made in artificial intelligence (AI) technology opens the door for a rethinking of the simulation modeling process for design and decision support. The problem solving as currently practiced in simulation modeling studies is essentially a search. The goal of the search is to find the combination of parameter values that will optimize the response values and the controllable values of the system. The burden of conducting that search and integrating the results of model behavior into a coherent solution currently rests with the human user. Much of the work in the AI field on automated reasoning has dealt with the inference engine and how to use the facts and rules contained in the knowledge base to conduct an efficient search for a solution. These developments will play a vital part in the design of new goal seeking, knowledge based simulation systems.” [200, p. 412].

It is clear that as model-based knowledge generation techniques, one with inferencing, the other by performing experiments, AI and simulation have a common feature. Both are based on search; only the nature of the search space and the way the search are performed are different.

With reference to the synergy of AI and simulation, reducing simulation to a mere “what-if...?” analysis [183] or to a “dumb” simulation [19] reflects the limitations of the wrong points of view rather than that of simulation.

The relationships of AI and simulation consists of two main domains: use of simulation in AI and use of AI in simulation. The former consists of two types of activities: cognitive simulation and use of simulation for other applications of AI such as the evaluation of knowledge based systems [27, p. 228]. Cognitive simulation is simulation of systems which have cognitive abilities. Such systems include humans [39], animals as studied in ethology [91], and a subset of non-biological systems with cognitive abilities such as autonomous robots [94].

The use of AI in simulation consists of AI-based simulation and AI-assisted simulation [219]. In AI-based simulation such as knowledge-based and qualitative simulations, the simulated behavior is generated by AI techniques. In AI-assisted simulation, AI techniques provide the computer assistance in areas such as model-base management or the formulation of models and/or simulation experiments. These are areas other than the generation of model behavior.

Currently (in the early 90s) the term AI in simulation is used to mean “knowledge-based simulation”, “rule-based simulation”, or “frame-based simulation”. Instead of the term “AI in simulation” or its synonym “intelligent simulation”, the term “cognizant simulation” can be used to denote simulation with cognitive abilities. Similarly, “cognizant simulation environment”, or “cognizant environment”, for short, can denote a simulation environment which has cognitive abilities. The choice of the terminology “cognizant simulation” may have several advantages: firstly, it may reflect yet another aspect of simulation which is a multifaceted field, rather than implying the addition of some techniques to it from another field such as artificial

intelligence. Secondly, the term “cognizant simulation” can detach simulation from a fundamental issue of AI of not having an all inclusive and concise definition of intelligence.

2. An inventory of the existing systems

The inventory of cognizant simulation systems is presented in two parts: by application areas and by the type of the environments.

2.1. APPLICATION AREAS

Table 1 provides a synopsis of the application areas of cognizant simulation discussed in over 100 publications. As is seen in table 1, four application areas received particular attention. They are: manufacturing (including flexible manufacturing), industrial processes, decision support, and military applications. Then comes circuits/devices, control systems, ecological systems, neurocomputing, and traffic studies. Some other application areas which benefited from AI in simulation are: agriculture, aircraft, autonomous vehicles, banking, biological/medical systems, building, cancer therapy, character handling, chemical reactions, computers, fault diagnosis and propagation, information systems, learning, maritime systems, networks, nuclear physics, self-organizing systems, social systems, software, space flight, and training/tutorial. Table 1 can be useful in finding out most major references in thirty application areas.

Almost half of the application-oriented documents covered in this study are published in the 90s. Considering the hundreds of application areas where traditional simulation is successfully applied (see for example, proceedings of the Summer, Winter, or European Simulation Conferences, as well as the Eastern, Western, and European Simulation Multiconferences; European Simulation Symposia; or the proceedings of the IMACS, Pittsburgh, or Florida conferences), there is no reason for this trend not to continue, to have a large number of application-oriented publications in the years to come. Especially, after studies already reported in the literature dealing with methodology as well as modelling and simulation tools or environments, it would be natural to have application-oriented publications to flourish.

2.2. TYPE OF THE ENVIRONMENTS

A tool provides a single or a small number of functionalities whereas an environment provides a more complete set of functionalities to support the activities of modelling and simulation life cycle [11]. A simulative system has simulation abilities in addition to other modelling abilities such as design, as it is the case in simulative VLSI design systems. In this section two major types of tools or environments are considered, namely those developed for specific application areas and the general purpose ones.

Table 1

Application areas of cognizant simulation.

Application areas	Author(s)	Year	Application areas	Author(s)	Year
Agriculture	Comis	1986	Industrial processes	Fujiwara, Sakaguchi	1986
	Jones	1986		Gaines	1986
Aircraft	Keskey, Skyes	1987		Juuso . . .	1990
	Rowland . . .	1993		Kitowski	1983
Autonomous vehicle	Blackemore . . .	1986		Reddy, S.M.	1990
	Glicksman	1986		Salgame . . .	1990
Banking	Coats	1990		Sun, Kaye, Chrystall	1991
Biological/medical systems				Vangheluwe . . .	1990
	Deutch, Futo, Papp	1986		Vansteenkiste . . .	1990
	Esakov, Badler	1991		Waye . . .	1989
	Van Braam . . .	1985	Information systems	Liu . . .	1990
Building	Soubra . . .	1993		Sakthivel . . .	1992
Cancer therapy	Langlotz . . .	1985	Inventory	Krumholz	1989
Character handling	Reilly, Anumolo	1991	Learning, Animal	Mueller . . .	1991
Chemical reactions	Eisenberg	1990	Learning, Human	Clema, Fynewewer	1973
Circuits/Devices			Manufacturing/FMS	Aldo, Mario	1990
	Benavides, Wyatt	1988		Arons	1990
	Herczeg, Herczeg	1989		Ben-Arieh	1986
	Keuneke	1990		Berenson	1986
	Mayoram, Pederson	1984		Brown . . .	1985
Computers	Cho, Kim, Cho	1990		Cochran . . .	1987
Control systems				Esposito . . .	1990
	Garrido, Neves	1990		Ford, Schroer	1987
	Lirov . . .	1988		Javor	1992
	Meijer, Kerckhoffs	1990		Joseph	1989
	Rao . . .	1987		Kachitvichyanakul . . .	1986
Decision support				Merkuryev . . .	1991
	Ahamed, Roman	1986		Reddy, Y.V.R. . . .	1980
	Anderson, Thorson	1982		Sathi . . .	1986
	Clema . . .	1973		Seliger . . .	1987
	Clymer	1991		Shannon	1988
	Feng	1992		Sun, Chrystall, Kaye	1991
	Feng, Deng	1992		Vansteenkiste . . .	1990
	Krumholz	1989		Wang, Bell	1992
	Moser	1986		Wu, Wysk	1987
	Petkovski	1988		Zalevsky	1988
Ecological systems			Maritime systems	Blackwell . . .	1991
	Andrews . . .	1984	Military	Ericson, Jr.	1986
	Jankowski	1989		Gunsch, Herbert	1983
	Loehle	1987		Hopple	1992
	Muetzzelfeld . . .	1986		Middleton . . .	1986
	Puccia, Levins	1991		Sokol . . .	1992
	Uschold . . .	1985		Tao, Wang	1992
Fault	Fortuna . . .	1993		Wise, Modjeski	1991
(diagnosis/propagation)	Grundspenkis	1993		Zhang . . .	1992
	Prager . . .	1989	Networks	Rozenblit . . .	1986
Industrial processes				Ruiz-Mier . . .	1985
	Abdulmajid . . .	1991	Neurocomputing	Cheng, Hu	1992
	Elmaghraby . . .	1985			
	Epstein	1986			
	Fjelheim	1985			

continues . . .

Table 1 (continued)

Application areas	Author(s)	Year	Application areas	Author(s)	Year
Neurocomputing	Fortuna . . .	1993	Space flight	Izygon, Pitman	1991
	Obaidat, Marchiarolo	1992		Kawamura	1985
	Weinroth . . .	1990		Lanier, Vizzier	1991
	Wnek, Springsteen	1990	Traffic	König . . .	1993
Nuclear physics	Selig . . .	1987		Santiago . . .	1990
	Farley, Clark	1954	Traffic, air	Gerstenfeld, Pan	1986
Self-organizing systems	Yukhimov . . .	1993	Traffic, train	Cheng	1992
				Rajput, Asthana	1990
Social systems	Elzas	1986b	Training/Tutorial	Draman	1990
	Liang, Tu	1989		Huang, Zhang, Li	1992
Software	Ragade . . .	1990		Keskey, Skyes	1987

Table 2a provides a list of over thirty environments which are developed for several application areas such as: agriculture, building, cancer treatment, decision support, ecology, genetics, industrial processes, integrated circuits, inventory, manufacturing, military, nuclear physics, reactor, space flight, traffic, training/tutorial, and validation/verification. Table 2b is a list of over thirty general purpose cognizant simulation environments. Some of the environments are characterized within the taxonomy which is presented in the next section.

3. A taxonomy and current realizations

A taxonomy of of AI-based simulation and AI-assisted simulation is useful for several reasons: one can perceive the unity of the field, one can classify the current achievements, and one can systematically explore promising new areas (by expanding or refining the classification scheme, if necessary). Other relevant taxonomies are developed by Hopple [95], Kwanjai and Wild [126], O'Keefe [155], Ören [157], Round [184], and Shannon et al. [201].

The taxonomy is based on two criteria: the *role of AI* in the synergy and whether or not a user can *directly access* the simulation or the AI component of the synergy. The *role of AI* in the synergy can be generation of model behavior; and knowledge processing for other purposes such as realization of user interface functions and other functions such as modelling, analysis, and validation and verification. A user can have *direct access* to the simulation system, to the knowledge-based system, or to both of them. Accordingly, the *integration* of AI and simulation systems can be sequential, parallel, or mixed. In a sequential access, a user can directly access either the simulation or the knowledge-based system. In a parallel access, a user can directly access both the simulation or the knowledge-based system. A mixed access is a parallel access where from the simulation system one can access a knowledge-based system and vice versa. In the sequel, taxonomies of AI-based simulation (or cognizant simulation) and environments for AI-assisted simulation (or cognizant simulation environments) are presented.

Table 2(a)

Artificial intelligence in simulation: Domain-specific environments.

Application area	Abbreviation	Name	Author	Year
Agriculture	COMAX	(Knowledge-based simulation for cotton crop management)	Comis . . .	1986
	VBC	(controlling) VelvetBean Caterpillar (infestation of soybean fields)		
Building Cancer treatment	ISE	Intelligent Simulation Environment	Soubra . . .	1993
	ONYX	(a knowledge-based simulation system for planning therapies)	Langlotz . . .	1985
Decision support	Can Build	(an inventory simulation tool)	Krumholz	1989
	EXYS	(a knowledge-based simulation system)	Moser	1986
	IEDSS	Intelligent Economic Decision Support System	Feng	1992
	MBDS	expert system technology in Model-Based Decision Support	Feng, Deng	1992
Ecology	BEHAVE	a fire BEHAViour prediction and fuel modeling system	Andrews . . .	1984
	ECO	intelligent front end for ECOlogical modelling	Muetzzelfeld . . .	1986
Genetics	QSOPS		Round	1987
	PEPTIDE		Weld	1985
Industrial processes	IPSE	Intelligent Process Simulation Environment	Reddy . . .	1989
	KIPS	Knowledge-based Interface to Process Simulation	Fjellheim	1986
	SIMSMART	sim. for automated control & optimization of complex industrial processes	Waye . . .	1989
	SPARKS	System Performance Analysis using Real-time knowledge-based Simulat	Salgame	1990
Integrated circuits	MARS		Singh	1983
Inventory	CAN BUILD		Krumholz	1989
Manufacturing	KBS	Knowledge-Based Simulation	Reddy, Fox	1980
	KBSIM	Knowlede-Based Simulator for FMS Scheduling & dispatching	Kachitvichyanakul	1986
	MOSYS	(a knowledge-based simulation system for flexible manufacturing	Seliger . . .	1987
	MPECS	an intelligent flexible machining cell controller	Wu, Wysk	1987
	SIMULATION CRAFT		Sathi . . .	1986
	STEM		AI Ltd.	1988
Military	ART-ROSS	ART-based Rule-Oriented Simulation System	McFall, Klahr	1986
	ICAT	Intelligent Control Air Combat Target	Tao, Wang	1992
	ISLE	Intelligent Scalable Logistics Environment	Sokol . . .	1992
	LCOM2000	Logistics COMposite	Hopple	1992
	SAD-1	Surface-to-Air Defence	Zhang	1992
	SONAR PLEXUS	(enhancing a command and control simulation with reasoning)	Halley	1987
Nuclear physics	ABLE	(knowledge-based control for particle accelerators)	Selig . . .	1987
Reactor	RTSE	Reactor Trip Simulation Environment	Epstein	1986
Space flight	ESDOTS	Expert System for Design, Operations, and Technology Studies	Lanier, Vizzier	1991

continues . . .

Table 2(a) (continued)

Traffic	NESS	NASA Expert Simulation System	Kanamura	1985
Traffic, train	PROROD		König . . .	1993
Training/Tutorial	IVIS	Intelligent Visual Interactive Simulator	Rajput, Asthana	1990
	MASCOT	Motorola Artificial Simulation Companion		
		Organizer and Teacher	Mackulal . . .	1989
Validation	TTESS	Tutorial Tool for Expert Supervised Simulations	Draman	1990
	MODVEX	an expert system for model validation and maintenance	McKinion	1986

Table 2(b)

Artificial intelligence in simulation: General purpose environments.

Abbreviation	Name	Author	Year
AES	Areté Engagement Simulator	Aronson	1992
BLOPS	an object-oriented language for simulation and reasoning	Middleton . . .	1986
CASSANDRA	Cognizant Adaptive Sim. System for Applications in Numerous . . .	Javor	1992
CAUSIM	rule-based CAUsal SIMulation system	Fu	1990
DESIRE	Dynamic Expert Systems in Real-time Environments	Vansteenkiste . . .	1992
DEVS-Scheme	Discrete EVent Simulation in Scheme	Zeigler	1986
DME	Device Modeling Environments	Iwasaki . . .	1992
E/Slam	Elucidation of Slam II programs	Ören	1993
EMMS	Expert Mathematical Modelling System	Zhao, Li	1989
ESP-Scheme	System Entity Structure in Scheme	Kim, Zeigler	1989
ESSMA	Expert System of Simulation Model building and Algorithm selection	Liu, Shen	1992
EZSIM		Khosnevis . . .	1987
HRS	Hierarchical Reasoning in knowledge-based Simulation	Nadoli . . .	1990
HYDRA	Hypothesis Deduction Through Rule Application	Groen . . .	1986
HI-SE	Integrated-Interactive-Intelligent Simulation Environment	Kim, M.H.	1992
KBMG	Knowledge-Based Model Construction	Murray, Sheppard	1988
KBDSE	Knowledge-Based Design and Simulation Environment	Rozenblit . . .	1990
KBMSE	Knowledge-Based Modelling and Simulation Environment	Rahbar . . .	1989
KBSE-I	Knowledge-Based Simulation Environment	Yizhi, Wen	1992
KDL	Knowledge/Data Language for query driven simulation	Kochut . . .	1991
KEMS	Knowledge-based Environment for Modelling and Simulation	Tanyi, Likens	1989
LOPPS	Logic Programming Processor for Simulation	Radiya, Sargent	1987
LOPS	Logic Programming Specification	Zajicek	1986
MaGest	Modelling Advisor for GEST(General System Theory Implementor)	Aytaç, Ören	1986
NLUS	Natural Language Understanding System	Doukidis . . .	1986
PROSS	PROlog Simulation System	O'Keefe . . .	1986
RBMS	Rule Based Modelling System	Marsh	1985
SESSA	Statistical Expert System for Simulation	Mellichamp . . .	1989
SIGMA	an intelligent and graphical system for the modelling of assembly systems	Brugnot . . .	1990
SIMGEN.MK2	(self-explanatory simulation)	Forbus . . .	1992
SimKit	knowledge-based simulation and modelling tools in KEE	Stelzner . . .	1989
SIMSTAT	(a tool for simulation analysis)	Blaisdell . . .	1992
SIPDES	a Simulation Program Debugger using an Expert System	Doukidis . . .	1991
SMPACK	an expert system included in a Simulation and Model processing PACKage	Xiong, Song	1986
STIPS	System Theory Instrumented Problem Solver	Pichler	1986
STRADS	STRategic Automatic Discovery System	Oresky . . .	1991
TRANS	an advisor for experimentation with TRANSaction flow models	O'Keefe	1986a

3.1. CATEGORIES OF COGNIZANT SIMULATION

Based on the two criteria, six major categories of cognizant simulation are identified as shown in figure 1a. They are: numerical simulation with nested neural nets, knowledge-based simulation, qualitative simulation, multiparadigm simulation, simulation with a nested knowledge-based system, and knowledge-based system with a nested simulation system.

All the categories discussed can be embedded in more comprehensive environments such as design or decision support systems [146, 216]. An important issue in the integration of simulation systems in decision support systems (to generate simulative decision support systems), is to consider simulation gaming (or operational gaming) as a type of simulation. Gaming simulations can be co-operative or competitive and are used especially in business or military training. In a simulation game, there are at least two teams, the members of each have limited knowledge about the model and normally do not know the decisions of the other team(s). Once each team makes its respective decisions, the model behavior is generated until it is interrupted. At this time some knowledge is made available to team members who make other decisions; and this intermittent simulation continues until a time limit or the occurrence of some important conditions such as bankruptcy or lost of total forces in a military environment. Davis [42] discusses application of AI in a military gaming. A reference to compare stochastic simulation and gaming within a decision support system (without any AI component) was given by Gray and Borovits [86].

3.1.1. *Simulation with nested neural nets*

A neural network is a collection of layers of connected knowledge processors; it provides connectionist knowledge processing. Each processor can have one or more inputs and one output. The output of one processor can be connected to one or more processors. Each processor may have a different weight factor associated with each input to control the contribution of that input. Layers other than input or output are called hidden layers. Three aspects characterize neural nets: node characteristics, node coupling, and weight adjusting rules. Node characteristics defines how inputs are processed and transformed into outputs. Node coupling defines how the processors are interconnected. The rules dynamically adjust the weight factors by learning. "Considering the most popular types of networks, the purpose of learning process is to adjust all the weights in the network so as to minimize the difference between the actual outputs of the network and their respective target output values for a set of example inputs called a training set." [220, p. 207]. The values of the inputs to a neural network can be continuous or binary. The learning in each category can be supervised or unsupervised. Accordingly, Lippmann's taxonomy [132] identifies the following four major categories of neural networks: Hopfield net (binary input, supervised learning), Carpenter–Grossberg classifier (binary input, unsupervised learning), perceptrons and multilayer perceptrons

Categories of cognizant simulation (AI-based simulation) (AI is used primarily for the generation of model behavior (kbSim, QSim, and kb1) and for learning (ML, NN))		User can have direct access to:	Integration of AI and simulation
1. Numerical simulation with <u>nested</u> neural nets		Simulation	Sequential
2. Knowledge-based simulation			
3. Qualitative simulation			
4. Multiparadigm simulation			
5. Simulation (numerical, knowledge-based, or qualitative) with a <u>nested</u> knowledge-based system			
6. Knowledge-based system with a <u>nested</u> simulation (numerical, knowledge-based, or qualitative) system (simulative knowledge-bd system)		Knowledge-based system (kb1)	

Figure 1a. Types of cognizant simulation.

(All of the categories can be embedded in more general design or decision support systems.)

- kb1 – Expert system (knowledge-based system) for the generation of model behavior.
- kbSim – Knowledge-based simulation system.
- ML – Machine learning module.
- NN – Neural net (optional in types 1, 2 and 4–8c).
- numSim – Numerical simulation system.
- QSim – Qualitative simulation system.
- u/i – User/system interface.
- – Optional.

(continuous input, supervised learning), and Kohonen self-organizing feature maps (continuous input, supervised learning).

The use of a neural network within a simulation system is reported by Padget and Roppel [166] and by Weinroth and Madey [228]. The prototype system developed by Weinroth and Madey is used to accelerate the execution time of complex simulations expressed in GPSS. The results of the neural net provide input to the simulation system. In the prototype, the neural network was developed and trained separately from the GPSS simulation.

Fortuna et al. [71] report a synergy of a numerical simulation and a neural net for the purpose of implementing an on-line fault diagnosis and control system for an induction motor. The on-line numerical simulator generates the “normal” behavior of an induction motor. Fault diagnosis and control can be made by referring to the normal behavior and the behavior of the motor filtered through a neural network. Once the comparison detects an indication of a fault, the intervention of an expert system is requested.

In simulations with neural nets, users can directly access only the simulation system. The simulation and a neural net would normally be integrated in a sequential way. In this case, the neural net can process part of the information available to the total system and can provide filtered information to the simulation system. Neural nets may be optional modules in other categories of cognizant simulations and cognizant simulation environments.

3.1.2. Knowledge-based simulation

Knowledge-based simulation is mostly a rule-based or frame-based simulation where generation of model behavior is performed by an inference engine; knowledge about the model and the experimental conditions are expressed as rules and facts, or frames. A knowledge-based system distinguishes a knowledge base (i.e., the knowledge expressed as a set of facts and rules) and the knowledge processing module which is called an inference engine. A rule consists of “a left side (pattern) that determines the applicability of the rule and a right side that describes the operation to be performed if the rule is applied” [182, p. 36]. This definition of a rule applies to forward rules. In a backward rule, the functions of left and right sides are reversed. In the simplest form, a rule is a conditional fact.

Early examples of knowledge-based simulation started with special simulation languages such as TS-Prolog and T-CP. TS-Prolog is a Prolog-based language for rule-based simulation [76]. T-CP is a simulation language based on concurrent Prolog [34]. An example of knowledge-based simulation is BEHAVE which is developed for the prediction of wildland fire behavior [5]. This category may also include models of intelligent agents [240]. Other references in knowledge-base simulation are [66, 68].

Ability to learn is an essential characteristics of intelligent systems. Carbonell [29] identifies four major paradigms for machine learning which are inductive, analogical, connectionist, and genetic paradigms. The role of connectionist paradigm

has been mentioned in the previous section. A knowledge-based system may have learning ability if it can update its knowledge base. Therefore, except the first case where there is no knowledge base, machine learning may be applied to all types of cognizant simulation as well as to cognizant simulation environments.

A recent study by Khoshnevis and Parisay [116] provides an example of a knowledge-based queueing simulation system nested with a machine learning module. Their system uses inductive learning for monitoring simulation experiments.

3.1.3. *Qualitative simulation*

Qualitative simulation is the generation of qualitative trajectories (i.e., time-ordered set of values of qualitative variables) by inferencing from qualitative models. A qualitative model is a model with qualitative variables. "Qualitative variables are variables that assume a finite ordered set of qualitative values" [30, p. 1087]. Some qualitative models are naive physics models [23] and inductive system models [120].

An early qualitative simulation study was QSIM [125]. Fishwick and Luker [67] cover qualitative simulation. Fishwick [65] elaborates on the terminology. Limitations of qualitative simulation have been elaborated on by Kuipers [125] and a critique is offered by Cellier [30].

3.1.4. *Multiparadigm simulation*

In multiparadigm simulation, two or more different simulation paradigms (namely, numerical simulation, knowledge-based simulation, and qualitative simulation) can be used to generate simulated model behavior in one application. (Multiparadigm modelling is distinct from multiformalism simulation where in a numerical simulation, more than one modelling formalism can be used to generate simulated model behavior; for example, finite state machines, and Petri nets can be used for different components of a complex model.) Neural nets and machine learning modules can also be integrated in such systems.

An interesting and promising realization of a multiparadigm simulation is reported by Forbus and Falkenhainer [70]. They combined qualitative and quantitative simulations to have a simulation system with self-explanation abilities. They name this type of simulation, self-explanatory simulation. An example question and system's answer are as follows:

"Q: What happens next?

A: At 238.6 seconds the boiling temperature of WATER and the temperature of the water in CAN become equal. Then, heat is flowing from STOVE to the water in CAN and the water in CAN is boiling." [70, p. 385].

Another multiparadigm simulation where qualitative and quantitative techniques have been used together for the simulation of chemical reaction mechanisms is reported by Eisenberg [51]. Soubra et al. [208] report a simulation environment

where different simulation tools can be integrated. They distinguish two possibilities that they identify as sequential coupling and pingpong coupling. In the first case, a simulation tool can activate a second simulation tool and can pass the necessary information. In the second case two simulation systems can work concurrently, passing each other relevant information.

Kerckhoffs' work prepares the basis for the synergy of multiparadigm simulation with neural nets. Kerckhoffs [110] and Kerckhoffs et al. [111] discuss the synergy of three types of model-based knowledge generation techniques, namely, experiential, connectionist, and symbolic knowledge processing. Experiential knowledge-processing ability is provided by numeric simulation; connectionist abilities are provided by neural networks; and symbolic knowledge processing is provided by inferencing systems such as expert systems (statistical inferencing is not yet taken into account). The qualifier "model-based" may become important when some autonomous or quasi-autonomous systems may also have the ability to perform experiments directly with real systems. Then, one can also consider knowledge generation based on experimentation with real systems which is not model-based.

3.1.5. Simulation with a nested knowledge-based system

In a single paradigm simulation (i.e., numerical simulation, knowledge-based simulation, or qualitative simulation) or in a multiparadigm simulation, simulation component(s) can have direct access to a knowledge-based module. As an implementation detail, the knowledge-based module may be distinct from the simulation module(s) or it may be embedded in one of them. In a simulation with a nested knowledge-based system, the simulation system may have an interrupt to ask and receive some knowledge from the nested or embedded knowledge-based module. The system can also be augmented by a neural net and learning module(s) for the knowledge-based components.

3.1.6. Knowledge-based system with a nested simulation system

Knowledge-based component is used to generate model behavior by non-experiential methods. User can not access directly the simulation component which is sequentially integrated with the AI component; the knowledge-based system can activate the (single or multiple paradigm) simulation system. The knowledge-based system can adapt its behavior based on the results passed to it automatically by the simulation system. The simulation system may also have direct link to a neural net. Machine learning components may be connected to the knowledge-based modules.

3.2. CATEGORIES OF COGNIZANT SIMULATION ENVIRONMENTS

A cognizant simulation environment (or a knowledge-based simulation environment, or an environment for AI-assisted simulation) supports a simulation study by using AI-based techniques (figure 1b). In such environments, at least one

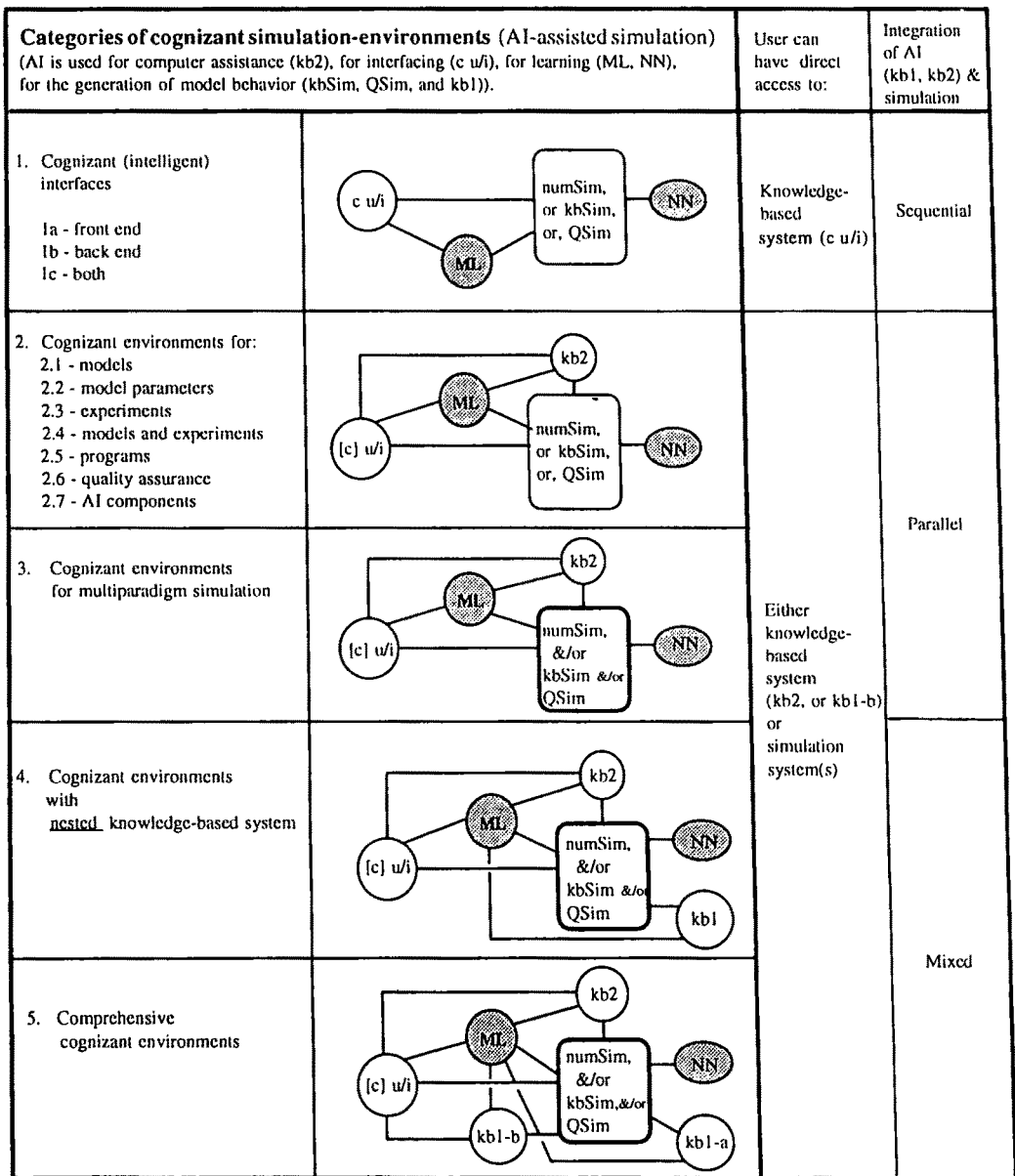


Figure 1b. Types of cognizant simulation environments.

(All of the categories can be embedded in more general design or decision support systems.)

(User interfaces can be conventional (u/i) or cognizant (c u/i).)

kb2 – Knowledge-based system is used for computer-assistance and not for generation of model behavior.

AI component exist for computer assistance to support user/system interface functions or other type of knowledge processing functions not related with the generation of model behavior. Expert system shells which can offer knowledge acquisition tools,

knowledge representation mechanisms, and reasoning and explanation abilities can be used for the implementation of knowledge-based components [182, p. 549]. Systems such as SimKit™ provide integrated set of general purpose modelling and simulation tools built in and on the Knowledge Engineering Environment® (KEE®) [209].

Cognizant environments include cognizant (intelligent) interfaces; cognizant environments for single paradigm and multiparadigm simulations (for models, model parameters, experiments, programs, quality assurance, and for AI components); cognizant environments with a nested knowledge-based system; and comprehensive cognizant environments.

In an epistemology of knowledge-based simulation Reddy [178] provides a mapping of AI and simulation concepts to clarify their relationships. For examples, he succinctly defines a demon as a conditional event which casts light to demon-driven simulation as advanced by Javor [103, 104].

All the categories of cognizant simulation environments may have cognizant interfaces and neural nets. Machine learning module(s) can be integrated for some or all of the knowledge-based modules.

3.2.1. Cognizant interfaces

Users can directly access only the knowledge-based system which acts as a cognizant interface [218]. Some cognizant interfaces have been referred to in the literature as intelligent interfaces [212]. The simulation and AI systems are integrated in a sequential way. The AI component, namely the interface, is not used to generate model behavior. Cognizant interfaces are conceivable for single paradigm and multiparadigm simulation studies.

The interface may be a front end, a back end, or both. Cognizant front ends are AI-based environments for simulation experimentation. The knowledge-based system can prepare knowledge for and activate the simulation component. Cognizant front ends include query formulation environments such as experiment specification environments, statistical experiment design environments, and experiment monitoring environments. They may also be coupled with a natural language processor to handle queries formulated in a natural language. Taylor and Hurriion [215] describe an expert advisor for simulation experiment design and analysis.

Cognizant back end interfaces consist of knowledge-based environments for simulation results. They can analyze the results and provide explanation of the results or generate output in a natural language. Hellman and Bahuguna [92] discuss explanation abilities for simulation. Austin and Khoshnevis [9], Beck and Fishwick [14], Fishwick [66], Reilly et al. [181] discuss natural language use in simulation. Based on the principle of management by exception, the interface should be able to filter the outcome to report only the pertinent aspect(s) of the results.

Mixed experimentation environments provide facilities to design experiments and to perform post-simulation analyses of the generated model behavior [96, 102, 154, 188].

3.2.2 Cognizant environments

A characteristic of cognizant (or knowledge-based) environments is that the AI component (kb2 in figure 1b) is used for reasons other than behavior generation and interfacing. The simulation and AI components are integrated in a parallel way. User can directly access either the simulation component or the AI component. Cognizant environments can support single paradigm as well as multiparadigm simulation. Knowledge-based environments provide a large class of possibilities for models, model parameters, experiments, simulation programs, for quality assurance of simulation studies, and for AI components.

- *Cognizant environments for models* and model parameters include:
 - modelling environments (where knowledge bases may hold knowledge about modelling formalisms, scientific laws, engineering or other domain specific formulas, and specific domain of application(s);
 - model-base management systems (where selection of appropriate models and model reusability can be facilitated);
 - model modification (or model maintenance) systems;
 - model analysis systems;
 - model understanding systems;
 - model documentation systems;
 - model transformation systems (which may include model simplification tools); and
 - parameter management systems.

Modelling environments concentrate on the knowledge-based model specification facilities. See for example Doukidis and Paul [48], Gao [79], and Gelsey [81]. Modelling environments should have a seamless interface between different tools and environments; otherwise their usability would be compromised. Zeigler et al. [241] discuss model base management. Campbell [28] reported an expert system for simulation model selection. Another reference to model selection is Ellman and Keane [52]. The system developed by Shrobe [203] extracts its understanding of mechanical linkages by analyzing the results of a numerical simulation of the mechanism.

- *Modelling and simulation environments* provide facilities to specify models as well as simulation experiments. Several environments fall under this category. For example, DEVS-Scheme [239] provides facilities for simulation with discrete event systems. KBS provides facilities to specify and simulate manufacturing systems [179]. DME (Device Modeling Environment) which is a model-based reasoning system, formulates a model based on the topological description of a device and simulates it based on the initial conditions [98]. For some other realizations, see Benavides and Wyatt [16], Fox et.al. [189], and Gallaire [78].

In modelling and simulation environments, modelling and experimentation can be sequential processes or can exist in a loop. In the first approach, a model, once specified, is not modified. In the latter approach, a model can be manually or automatically tailored based on the results of the simulation experiments. In a design environment, these possibilities correspond to cases where simulation is used to test a design and to provide feed-back to manually or automatically modify a design, respectively.

MOSYS [197], which is an environment for flexible manufacturing, is an example to a knowledge-based environment with dynamic model modification ability. In MOSYS, models are rule-based and expressed in Prolog. A model consists of the functional and topological descriptions of a system. The functional specification can use one of the five functional building blocks to represent manufacturing, assembling, transporting, testing, and storing. The topological description represents the physical layout of the functional blocks and their interconnections. The dynamic model modification aspect of MOSYS can generate proposals for the refinement of a model, based on the outcomes of a simulation run and the goal of the simulation study.

- *Environments and tools for symbolic processing* of models and experiments provide symbolic processing abilities as supported by Computer-Aided Systems Technology (CAST) [169] and Computer-Based Systems Engineering (CBSE). For example, Overstreet and Nance [165] provided the basis for a discrete event simplification tool. It is hoped that research will continue in this very important and promising field.

- *Cognizant environments for simulation programs* include automatic program generation systems from problem-oriented high level specifications and program understanding systems. Murray discusses automatic programming for simulation. Li and Zhao [130] use analogical reasoning as a mechanism for the generation of programs.

- *Cognizant environments for quality assurance* include validation/verification environments which are based on knowledge-based techniques. Ören [160] provides a systematization of the quality assurance paradigms for AI in Modelling and Simulation. An early realization is MAGEST [10] which can certify the acceptability of a model with respect to a set of modelling formalism criteria [163]. Deslandres and Pierreval [45] discuss an expert system architecture for the statistical validation of simulation models. In a recent study, consistency of a simulation program which is generated by a program generator component of a simulation program understanding system is assured by transforming the internal representation of the synthesized Slam II program into a set of Prolog facts which is processed together with an appropriate rule base [229]. As pointed out by Forbus and Falkenhainer [70], mixed qualitative and numerical simulations may provide self-monitoring abilities to

automatically detect unacceptable values of some variables, such as a negative mass, a negative machining time, or a temperature below the absolute temperature.

Zeigler et al. [242] stress the fact that computer-aided validation can be achieved only on the foundation of a firm framework of formal concepts offering a standard vocabulary and definition. The experimental frame they discuss [242, p. 331] includes summary mappings which are statistical and other aggregations of the input-output behavior into reduced and manageable spaces. The goal of modelling (which is used in the mapping of a select aspect of reality to a model), is implicit in the concept of summary mappings. Future methodologies should make the goal of modelling as well as performance measures explicit in order to treat the relevance and validity of models in a systematic way.

Iwasaki and Chandrasekaran [98] use simulation and functional knowledge for design verification. Some other references in this very important area are De Mori and Prager [43], Deng and Jenkins [44], Findler and Mazur [64], Sargent [193], and Schnepf [195].

3.2.3. Cognizant environments with a nested knowledge-based system

This category of cognizant environments corresponds to the AI support in single or multiparadigm simulations where simulation module(s) can have interrupts to access a knowledge-based module (kb1 in figure 1b) to receive some values. The access of the simulation module(s) to the knowledge-based component is sequential. AI is used for mixed purposes, namely for behavior generation (kbSim, QSim, and kb1) and for other purposes (kb2). Therefore, these environments can be named mixed environments. They can have cognizent interfaces. Their simulation modules can access neural nets and their knowledge-base modules can be enhanced by machine learning modules. As shown in figure 1b, machine learning can be used for the knowledge bases of: cognizant interfaces, knowledge-based simulation, qualitative simulation, non-experiential knowledge generation modules such as kb1, and other knowledge-based functions such as kb2.

3.2.4. Comprehensive, cognizant, environments

The essential characteristics of this category of knowledge-based environments is that a knowledge-based module (kb1-b in figure 1b) can access simulation module(s). Additionally, a simulation module may access a neural net or another knowledge-based module for behavior generation (kb1-a). Knowledge-bases may be enhanced by machine learning modules. Computer assistance provided by the AI environment (kb2) may include several functions of a cognizent environment.

SIMULATION CRAFT [12] is an example of a comprehensive environment where knowledge-based techniques are used to build, execute, and analyse the models. A dynamic planner is also used in SIMULATION CRAFT. Similarly, in

KBS (Knowledge-Based Simulation system) [72], AI assistance is provided to automate the simulation life cycle. Goal-directed reasoning modules are provided to identify subtasks to be performed, to initiate them at appropriate times, to identify their completions as well as the completion of the entire goal. The learning module and a causal analysis module can be used, sequentially, when the goal is to detect causal relationships within the model.

Kim [112] identifies the major components of another comprehensive environment, i.e., III-SE (Integrated Interactive Intelligent Simulation Environment) as the cognizant user interface, modelling, experimentation, and software environments, the knowledge bases (for models, experimentations, and software), and the data base. The modelling environment includes a modelling advisor and an EPN (Extended Petri Net) processor.

4. Promising areas of research

To reveal the important areas of research, merely a descriptive state-of-the-art analysis is not sufficient; one has to explore the domain of possible systems. This is why a taxonomy has been developed to fit existing realizations and to systematically explore new and promising directions of research and development. Basically, almost all of the categories of cognizant simulation and cognizant simulation environments offer challenges for further research and development. Some additional possibilities are outlined in the sequel.

4.1. KNOWLEDGE BASES FOR COGNIZANT SIMULATION

Three categories of knowledge bases are needed for:

- (1) Methodology or theory-based modelling, model processing, experimentation, behavior generation, and behavior processing. Even though system theories have already been successfully used in simulation, still a large number of possibilities of computer aided system theory applications can be integrated within simulation environments [169].
- (2) Domain-specific knowledge to accumulate knowledge of different application areas.
- (3) Model bases for single and multiformalism modelling environments to promote both model re-use with certified and uncertified models; and model maintenance where the modifications would be at model level and not at code level. The latter implies that the compilable versions of the high level specifications would be generated by program generators. Eliminating throw away modelling where models embedded in computer programs have to be respecified in similar yet different studies would put an end to the waste of intellectual efforts and misuse of valuable information resources. Institutions would benefit

from the accumulated knowledge where the specialists would tailor existing models (and add them to the model base) instead of respecifying them from scratch every time. Deciding on the usability of models under different conditions and model integrity (under changing conditions or for models undergoing mutations) are two major problems to be resolved for model bases.

Knowledge in different types of knowledge bases would also enhance the abilities of cognizant simulation environments to provide better guidance, recommendation, advice, explanation, justification, and rationale for actions taken, suggested or taken.

The representation of the knowledge in these knowledge bases should be such that they should be readable, understandable, and auditable by humans (with appropriate software tools, if necessary). After the accumulation of these types of knowledge, we can claim to have reached the second generation of environments with knowledge bases which would be reusable and maintainable as well as auditable and defensible, and hence reliable.

4.2. RELIABILITY ISSUES IN COGNIZANT SIMULATION

Several types of reliability issues, such as validation and verification have been very important in simulation. Application of AI in reliability issues, such as model validation and verification as well as quality assurance issues in cognizant simulation are still open areas. One should be aware of the fact that AI component of a simulation system may bring new sources of errors.

Reliability issues may be grouped under three categories for:

- (1) Specifications of models, model parameters, experiments, behavior generation, and behavior processing.
- (2) Programs.
- (3) Knowledge bases and knowledge base management systems [158]. The issues include those related with model bases, domain specific knowledge bases, methodology-based knowledge bases, and those related with data bases (such as data integrity).

4.3. ADVANCED QUERY SYSTEMS FOR COGNIZANT SIMULATION

Advanced query systems might provide cognizant front ends or back ends, or shells for simulation systems. There are several categories of issues to be addressed:

- (1) Abilities to ask questions, to generate knowledge, and to decide whether or not the generated knowledge is acceptable, can be part of the elevated goals for cognizant simulative systems. No intelligence would be devoid of the ability to ask questions. One would expect that the future generation of

cognizant simulation or simulative systems will be able to ask questions, formulate hypotheses, formulate the query for and initiate a simulation study, monitor the simulation execution, collect and analyze the results, and refute, accept, or refine the formulated hypothesis. A cognizant simulation system should then decide and justify the acceptability of the knowledge thus gained, based on a vast knowledge base. Then, it should either advise a human or directly use the knowledge thus gained.

- (2) An advanced query system would have the following advanced computer-aided abilities for: experimentation specification, formulation of the performance metric necessary to compare results of several simulation runs (based on the goal of the simulation study), experiment design, and analysis of results.

4.4. MACHINE LEARNING THROUGH SIMULATION

One can use simulation as model-based experiential knowledge generation technique for machine learning. In such simulative learning systems, special modules can design, run and monitor simulation experiments. Other modules can interpret the outcomes to learn about the structure or the behavior of the system under study. Some such possibilities were covered in an early article [159].

4.5. INTELLIGENT TRAINING SYSTEMS

Intelligent training and tutoring systems are cognizant simulators used for training and tutoring purposes. They include (1) appropriate knowledge bases; (2) a student model, for example, to track and rectify the learner's knowledge gaps and misconceptions; and (3) a tutor module to reflect one or more pedagogical templates, such as Socratic approach. Two other important research directions are the use of virtual reality in conjunction with cognizant environments and the use of cognizant decision support systems with simulation gaming abilities.

4.6. REPOSITORY-BASED COGNIZANT SIMULATION ENVIRONMENTS

Multiparadigm simulation and multiformalism simulation will support several functions through the tools and environments developed by different groups. These environments will be preferably open systems; therefore, instead of being just integrated environments, they may become integrative, allowing the installation of future tools and environments. The problem of the complexity of interfacing the tools and environments, which exists in computer aided software engineering, may emerge for comprehensive environments. In this case, a possible solution will be to have repository-based simulation environments [162]. Automated tool and environment installation as well as automated view translations would benefit from typical AI techniques.

5. Conclusions

As of the end of 1994, there is already a solid accumulation of AI applications in simulation. However, the caution expressed by Reddy is still applicable: "The phrases artificial intelligence and knowledge based seem to imply that systems based on these concepts are so powerful that complex problems can be solved with little effort on the part of the user. Many have learned, the hard way, that the use of AI programming paradigms does not automatically make a system powerful, but these programming paradigms do open up new possibilities for building powerful systems." [178, p. 162].

Acknowledgements

Some of my recent research, such as E/Slam (Elucidation of Slam programs), SimAd (Simulation Advisor), and RISE (Repository-based Integrative Software Environment) have been done for Bell Canada under contract. Their sponsorship is gratefully acknowledged. The detailed comments of the anonymous referees are also much appreciated.

References

- [1] B.A. Abdulmajid and R.J. Wynne, Embedded qualitative simulation for process control, *Proc. Summer Computer Simulation Con.* (1991) pp. 369–374.
- [2] S.V. Ahamed and E.G. Roman, A model-based expert system for decision support in negotiating, in: *Modelling and Simulation Methodology in the Artificial Intelligence Era*, ed. M.S. Elzas, T.I. Ören and B.P. Zeigler (North-Holland, Amsterdam, 1986) pp. 339–352.
- [3] E. Aldo and V. Mario, A Prolog simulator for FMS design and management, *Proc. AI and Simulation, Simulation Series 22 SCSI*, San Diego, CA, 1990) pp. 41–46.
- [4] P.A. Anderson and S.J. Thorson, Systems simulation – Artificial intelligence based simulations of foreign policy decision making, *Behav. Sci.* 27(1982)176–193.
- [5] P.L. Andrews and D.J. Latham, BEHAVE: A knowledge-based expert system for predicting wildland fire behavior, *Proc. Summer Computer Simulation Con.* (1984) pp. 1213–1218.
- [6] H. de S. Arons, Real-time expert scheduling in manufacturing, *Proc. European Simulation Symp.* (1990) pp. 124–127.
- [7] J.S. Aronson, AES: An object-oriented, knowledge-based approach to simulation, *Proc. Summer Computer Simulation Conf.* (1992), pp. 375–379.
- [8] Artificial Intelligence Ltd., *STEM User Guide* (Artificial Intelligence Ltd., Watford, England, 1988).
- [9] W.M. Austin and B. Khoshnevis, Qualitative modeling using natural language: An application in system dynamics, in: *Qualitative Simulation Modeling and Analysis*, ed. P.A. Fishwick and P.A. Luker (Springer, New York, 1991) pp. 263–301.
- [10] K.Z. Aytaç and T.I. Ören, MAGEST: A model-based advisor and certifier for GEST programs, in: *Modelling and Simulation Methodology Artificial Intelligence Era*, ed. M.S. Elzas, T.I. Ören and B.P. Zeigler (North-Holland, Amsterdam, 1986) pp. 299–307.
- [11] O. Balci, Guidelines for successful simulation studies, *Proc. Winter Simulation Conf.* (1991) pp. 25–32.
- [12] V. Baskaran, M. Fox, N. Sathi and J. Bouer, SIMULATION CRAFT: An artificial intelligence approach to simulation model creation, *Proc. IASTED Conf.* (1986).

- [13] H.W. Beck and P.A. Fishwick, Incorporating natural language descriptions into modelling and simulation, Technical Report TR-88-6, Univ. of Florida, Dept. of Computer and Information Sciences, Gainesville, FL (1988).
- [14] H.W. Beck and P.A. Fishwick, Natural language, cognitive models and simulation, in: *Qualitative Simulation Modeling and Analysis*, ed. P.A. Fishwick and P.A. Luker (Springer, New York, 1991) pp. 302–325.
- [15] D. Ben-Arieh, A knowledge-based system for simulation and control of a CIM, *Proc. 2nd Int. Conf. on Simulation in Manufacturing* (1986) pp. 13–21.
- [16] J.A. Benavides and D.L. Wyatt, Improving digital circuit simulation: A knowledge based approach, *Proc. Summer Computer Simulation Conf.* (1988) pp. 364–371.
- [17] S. Bennett, M.T. Rahbar, D.A. Linkens, E. Tany and M. Smith, Knowledge-based environment for modelling and simulation (KEMS), *Proc. SCS Western Multiconf.*, Simulation Series, 20:3 (SCSI, San Diego, CA, 1989) pp. 62–651.
- [18] R. Berenson, Wrapping AI techniques around simulation and other operations research tools to help manufacturing managers, *Proc. First AAAI Workshop on Artificial Intelligence and Simulation* (1986) Article No. 59.
- [19] J.E. Biegel and R.V. Rogers, Intelligent simulations, *Proc. Summer Computer Simulation Conf.* (1990) pp. 653–659.
- [20] G.K. Blackwell, J. Rangachari and C.T. Stockel, An intelligent interactive environment for a maritime real-time expert system, *Proc. Summer Computer Simulation Conf.* (1991) pp. 358–363.
- [21] W.E. Blaisdel and J. Haddock, SIMSTAT: A tool for simulation analysis, *Proc. Winter Simulation Conf.* (1992) pp. 421–425.
- [22] J.W. Blakemore, S.B. Dolins and P.R. Thrift, A general purpose robotic vehicle simulator, in: *AI Applied to Simulation*, ed. E.J.H. Kerckhoffs, G.C. Vansteenkiste and B.P. Zeigler, Simulation Series 18:1 (SCSI, San Diego, CA, 1986) pp. 151–161.
- [23] D.G. Bobrow, *Qualitative Reasoning About Physical Systems* (MIT Press, Cambridge, MA, 1985).
- [24] J.H. Bradley, Artificial intelligence in simulators: Intention, implementation, falsification and contingency, *Simulators VIII Simulation Series 24:1* (SCSI, San Diego, CA, 1991).
- [25] D. Breugnot, M. Gourgand and P. Kellert, SIGMA: An intelligent and graphical system for the modelling of assembly systems, *Proc. European Simulation Symp.* (1990) pp. 225–230.
- [26] T. Brown et al., Demonstration of an expert system for manufacturing process control, in: *AI, Graphics and Simulation*, ed. G. Birtwistle (SCSI, San Diego, CA, 1985) pp. 110–113.
- [27] J. Byleckie, The application of simulation to the validation of knowledge-based systems, *Proc. Summer Computer Simulation Conf.* (1993) pp. 228–231.
- [28] R.A. Campbell, Development of an expert system for simulation model selection, *Proc. Intelligent Simulation Environments*, Simulation Series 17:1 (SCSI, San Diego, CA, 1986) pp. 121–122.
- [29] J.G. Carbonell, Introduction: Paradigms for machine learning, *Art. Int.* 40(1989)1–9.
- [30] F.E. Cellier, Qualitative modeling and simulation: Promise and illusion, *Proc. Winter Simulation Conf.* (1991) pp. 1086–1090.
- [31] Y. Cheng, Rule-based train traffic rearrangement interactive simulator, *Proc. 2nd Beijing Int. Conf. on System Simulation and Scientific Computing* (1992) pp. 681–685.
- [32] Y. Cheng and S. Hu, Simulating liquor-tasting expert by neural computer, *Proc. 2nd Beijing Int. Conf. on System Simulation and Scientific Computing* (1992) pp. 4–6.
- [33] K. Cho, K. Kim and H. Cho, An intelligent environment for computer system design, *Proc. AI and Simulation*, Simulation Series 22:3 (SCSI, San Diego, CA, 1990) pp. 59–64.
- [34] J. Cleary, K.-S. Goh and B. Unger, Discrete event simulation in Prolog, *Proc. of Artificial Intelligence, Graphics and Simulation* (1985) pp. 8–13.
- [35] J.K. Clema and M.S. Fynewever, The simulation of human learning and human decision making, *Proc. 6th Annual Simulation Symp.* (1973) pp. 96–115.
- [36] J.R. Clymer, Simulation and design of artificially intelligent/adaptive decision making in systems, *Proc. Artificial Intelligence and Simulation*, Simulation Series 23:4 (SCSI, San Diego, CA, 1991) pp. 83–92.

- [37] P.E. Coats, Combining an expert system with simulation to enhance planning for banking networks, *Simulation* 50(1990)253–264.
- [38] J.K. Cochran, G.T. Mackulak, D. Castillo and E. Du, Configuring available software into an AI/ES environment for automated manufacturing simulation design on the PC, *Proc. Simulation of Computer Integrated Manufacturing Systems and Robotics*, San Diego, CA (1987).
- [39] A.G. Cohn, *Proc. 5th Conf. of the Society for the Study of Artificial Intelligence and Simulation of Behaviour* (Pitman, London, England; and Morgan Kaufmann, Palo Alto, CA, 1989).
- [40] D. Comis, When Comax speaks, farmers listen, *Agricult. Res.*(1986)6–10.
- [41] P.J. Davis and R. Hersh, *Descartes' Dream – The World According to Mathematics* (Harcourt Brace Jovanovich, San Diego, CA, 1986).
- [42] P.K. Davis, Applying artificial intelligence techniques to strategic-level gaming and simulation, in: *Modelling and Simulation Methodology in the Artificial Intelligence Era*, ed. M.S. Elzas, T.I. Ören and B.P. Zeigler (North-Holland, Amsterdam, 1986) pp. 315–338.
- [43] R. De Mori and R. Prager, Verification of flight simulators using a knowledge based system, *Proc. European Simulation Multiconf.* (1988) pp. 403–409.
- [44] D. Deng and J.O. Jenkins, Artificial intelligence validation of simulation models, *Proc. AI and Simulation, Simulation Series 20:4* (SCSI, San Diego, CA, 1989) pp. 80–84.
- [45] V. Deslandres and H. Pierreval, An expert system prototype assisting the statistical validation of simulation models, *Simulation* 56(1991)79–89.
- [46] T. Deutch, I. Futo and I. Papp, The use of TC-Prolog for medical simulation, *Proc. of Intelligent Simulation Environments* (1986) pp. 299–334.
- [47] G.I. Doukidis and R.J. Paul, Experiences in automating the formulation of discrete event simulation models, in: *AI Applied to Simulation*, ed. E.J.H. Kerckhoffs, G.C. Vansteenkiste and B.P. Zeigler, *Simulation Series 18:1* (SCSI, San Diego, CA, 1986) pp 79–90.
- [48] G.I. Doukidis and R.J. Paul, SIPDES: A simulation program debugger using an expert system, *Expert Syst. Appl.* 2(1992)153–165.
- [49] M. Draman, TTESS: A tutorial tool for expert supervised simulations, Ph.D. Thesis, Univ. of Central Florida (1990).
- [50] A.-M. Dubois, A draft of a component model library manager, The “MODELOTHEQUE”: Analysis of an approach and first results, in: *Systems Analysis and Simulation II – Applications*, ed. A. Sydow, S.G. Tzafestas and R. Vichnevetsky (Springer, New York, 1988) pp. 396–403.
- [51] M. Eisenberg, Combining qualitative and quantitative techniques in the simulation of chemical reaction mechanisms, *Proc. AI and Simulation, Simulation Series 22:3* (SCSI, San Diego, CA, 1990) pp. 233–242.
- [52] T. Ellman and J. Keane, Intelligent model selection for hillclimbing search in computer-aided design, in: *Design from Principles, Papers from the 1992 Fall Symp.* (AAAI Press, Menlo Park, CA, 1992) pp. 119–124.
- [53] A.S. Elmaghraby and V. Jagannathan, An expert system for simulationists – Problems, experiences, lessons, in: *AI, Graphics and Simulation*, ed. G. Birtwistle (SCSI, San Diego, CA, 1985) pp. 106–109.
- [54] M.S. Elzas, Artificial Intelligence and modelling of societal systems: A synopsis, in: *Modelling and Simulation Methodology in the Artificial Intelligence Era*, ed. M.S. Elzas, T.I. Ören and B.P. Zeigler (North-Holland, Amsterdam, 1986) pp. 311–314).
- [55] M.S. Elzas, T.I. Ören and B.P. Zeigler (eds.), *Modelling and Simulation Methodology in the Artificial Intelligence Era* (North-Holland, Amsterdam, 1986).
- [56] M.S. Elzas, T.I. Ören and B.P. Zeigler (eds.), *Modelling and Simulation Methodology: Knowledge Systems' Paradigms* (North-Holland, Amsterdam, 1989).
- [57] S.A. Epstein, RTSE: The reactor trip simulation environment, *Proc. 1st. AAAI Workshop on Artificial Intelligence and Simulation* (AAAI, Menlo Park, CA, 1986), Article No. 51.
- [58] S.A. Erickson, Jr., Fusing AI and simulation in military modelling, in: *AI Applied to Simulation*, ed. E.J.H. Kerckhoffs, G.C. Vansteenkiste and B.P. Zeigler, *Simulation Series 18:1* (SCSI, San Diego, CA, 1986) pp. 140–150.

- [59] J. Esakov and N.I. Badler, An architecture for high-level human task animation control, in: *Knowledge-Based Simulation: Methodology and Application*, ed. P.A. Fishwick and R.B. Modjeski (Springer, New York, 1991) pp. 162–199.
- [60] A. Esposito and M. Vento, A Prolog simulator for FMS design and management, *Proc. AI and Simulation*, Simulation Series 22:3 (SCSI, San Diego, CA, 1990) pp. 41–46.
- [61] B.G. Farley and W.A. Clark, Simulation of self-organizing systems by digital computer, *Trans. IRE PGIT-4*(1954)76–84.
- [62] S. Feng, A simulation model-based Intelligent Economic Decision Support System (IEDSS), *Proc. 2nd. Beijing Int. Conf. on System Simulation and Scientific Computing* (1992) pp. 295–298.
- [63] S. Feng and S. Deng, ES technology in Model-based Decision Support (MBDS), *Proc. 2nd Beijing Int. Conf. on System Simulation and Scientific Computing* (1992) pp. 304–308.
- [64] N.V. Findler and N.M. Mazur, A system for automatic model verification and validation, *Trans. Comp. Sim.* 6(1990)153–172.
- [65] P.A. Fishwick, A study of terminology and issues in qualitative simulation, *Simulation* 52(1989)5–9.
- [66] P.A. Fishwick, A case study of natural language text generation for simulation analysis, *Proc. AI and Simulation*, Simulation Series 22:3 (SCSI, San Diego, CA, 1990) pp. 205–210.
- [67] P.A. Fishwick and P.A. Liker, *Qualitative Simulation Modeling and Analysis* (Springer, New York, 1991).
- [68] P.A. Fishwick and R.B. Modjeski (eds.), *Knowledge Based Simulation: Methodology and Application* (Springer, New York, 1991).
- [69] R.A. Fjelheim, A Knowledge-based interface to process simulation, *AI Applied to Simulation*, ed. E.J.H. Kerckhoffs, G.C. Vansteenkiste and B.P. Zeigler, Simulation Series 18:1 (SCSI, San Diego, CA, 1986) pp. 97–102.
- [70] K.D. Forbus and B. Falkenhainer, Self-explanatory simulations: An integration of qualitative and quantitative knowledge, *Proc. 8th National Conf. on Artificial Intelligence* (1991) pp. 380–387.
- [71] L. Fortuna, A. Gallo, G. Nunnari and L. Occhipinti, Fast simulation of an induction motor using neural networks: An application to fault diagnosis, *Proc. European Simulation Multiconf.* (1993) pp. 235–239.
- [72] M.S. Fox, N. Husain, M. McRoberts and Y.V. Reddy, Knowledge-based simulation: An artificial intelligence approach to system modeling and automating the simulation life cycle, in: *Artificial Intelligence, Simulation and Modeling*, ed. L.E. Widman, K.A. Loparo and N.R. Nielsen (Wiley, New York, 1989) pp. 447–486.
- [73] M.V. Frank and S.A. Epstein, Application of artificial intelligence to improve plant availability, in: *Intelligent Simulation Environments*, ed. P.A. Luker and H.H. Adelsberger, Simulation Series 17:1 (SCSCI, San Diego, CA, 1986) pp. 92–97.
- [74] L.-M. Fu, CAUSIM: A rule-based causal simulation system, *Trans. Comp. Simul.* 7(1990)251–264.
- [75] R. Fujiwara and T. Sakaguchi, An expert system for power system planning, *Proc. European Conf., Simulation Series* 18:1 (SCSI, San Diego, CA, 1986) pp. 174–177.
- [76] I. Futo and T. Gergely, TS-PROLOG: A logic simulation language, *Trans. Soc. Comp. Simul.* 3(1987)319–335.
- [77] B.R. Gaines, Expert systems and simulation in industrial applications, *Proc. Intelligent Simulation Environments*, Simulation Series 17:1 (SCSI, San Diego, CA, 1986) pp. 144–149.
- [78] H. Gallaire, A knowledge-based modelling and simulation tool, in: *Modelling and Simulation Methodology: Knowledge Systems' Paradigms*, ed. M.S. Elzas, T.I. Ören and B.P. Zeigler (North-Holland, Amsterdam, 1989) pp. 209–219.
- [79] C-B. Gao, A novel intelligent modelling software on Turbo-Prolog, *Proc. Beijing Int. Conf. on System Simulation and Scientific Computing*, Vol. 1 (1989) pp. 496–499.
- [80] P. Garrido and J. Neves, A control systems simulation methodology in concurrent Prolog, *Proc. European Simulation Symp.* (1990) pp. 21–25.
- [81] A. Gelsey, From CAD/CAM to simulation: Automatic model generation for mechanical devices, in: *Knowledge Based Simulation: Methodology and Application*, ed. P.A. Fishwick and R.B. Modjeski (Springer, New York, 1991) pp. 108–132.

- [82] A. Gerstenfeld and Y. Pan, Qualitative simulation: A focus on air traffic control, *Proc. 1st AAAI Workshop on Artificial Intelligence and Simulation* (1986) Article No. 1.
- [83] J. Glicksman, A simulator environment for an autonomous land vehicle, in: *Intelligent Simulation Environment*, ed. P.A. Luker and H.H. Adelsberger, Simulation Series 17:1 (SCSI, San Diego, CA, 1986) pp. 53–57.
- [84] A.J. Gonzales and D.D. Dankel, *The Engineering of Knowledge-Based Systems: Theory and Practice*, (Prentice-Hall, Englewood Cliffs, NJ, 1993).
- [85] I.J. Good, *Speculation Concerning the First Ultra-Intelligent Machine* (Institute for Defence Analyses, Princeton, NJ, 1964).
- [86] P. Gray and I. Borovits, The contrasting roles of Monte Carlo simulation and gaming in decision support systems, *Simulation* 47(1986)233–239.
- [87] A. Groen et al., The integration of simulation and knowledge-based systems, in: *AI Applied to Simulation*, ed. E.J.H. Kerckhoffs, G.C. Vansteenkiste and B.P. Zeigler, Simulation Series 18:1 (SCSI, San Diego, CA, 1986) pp. 189–197.
- [88] J. Grundspenkis, The use of knowledge based approach for simulation of fault propagation in complex technical systems, *Proc. European Simulation Multiconf.* (1993) pp. 217–221.
- [89] G.H. Gunsch and B.V. Herbert, A proposed military planning task simulator using the ROSS language, M.S. Thesis, AFIT/GE/EE/83D-24, Air Force Institute of Technology, Wright-Patterson AFB, OH (1983).
- [90] M.R. Halley, T. Miller, C. Hougum and W. Mosenthal, SONAR PLEXUS – Enhancing a command and control simulation with reasoning, *Proc. Simulators Conf.* (1987) pp. 15–18.
- [91] R. Harre and R. Lamb (eds.), *The Dictionary of Ethology and Animal Learning* (MIT Press, Cambridge, MA, 1986).
- [92] D.H. Hellman and A. Bahuguna, Explanation systems for computer simulations, *Proc. 1986 Winter Simulation Conf.* (1986) pp. 453–459.
- [93] J. Herczeg and M. Herczeg, A knowledge-based simulation for electronics circuits, *Simulation Digest* 19(1989).
- [94] L.O. Hertzberger and F.C.A. Groen (eds.), *Intelligent Autonomous Systems* (North-Holland, Amsterdam, 1987).
- [95] G.W. Hopple, Artificial intelligence and simulation: An application to logistics modeling, in: *Applied Artificial Intelligence: A Sourcebook*, ed. S.J. Andriole and G.W. Hopple (McGraw-Hill, New York, 1992) pp. 283–297.
- [96] J. Hu and J.W. Rozenblit, Towards automatic generation of experimental frame in simulation-based system design, *Proc. AI and Simulation*, Simulation Series 20:1 (SCSI, San Diego, CA, 1988) pp. 1–6.
- [97] X.-X. Huang, Z.-l. Zhang and H. Li, Application of expert system in achievement grading for the training simulator, *Proc. 2nd Beijing Int. Conf. on System Simulation and Scientific Computing* (1992) pp. 280–284.
- [98] Y. Iwasaki and B. Chandrasekaran, Design verification using functional knowledge, in: *Papers from the 1992 AAAI Fall Symp. on Design from Principles*, Technical Report FS-92-03 (AAAI Press, 1992) pp. 56–61.
- [99] Y. Iwasaki and C.M. Low, Device modeling environment: An integrated model- formulation and simulation environment for continuous and discrete phenomena, *Proc. 1st Int. Conf. on Intelligent Systems Engineering* (1992).
- [100] M. Izygon and C.L. Pitman, A knowledge-based front-end for a complex space flight simulation program, in: *Proc. Summer Computer Simulation Conf.* (1991) pp. 364–368.
- [101] P.L. Jankowski, Knowledge-based structured modelling: An application to stream water quality management, Ph.D. Dissertation, University of Washington, Seattle (1989).
- [102] A. Jávör, Applications of expert systems concepts to adaptive experimentation with models, in: *Modelling and Simulation Methodology in the Artificial Intelligence Era*, ed. M.S. Elzas, T.I. Ören and B.P. Zeigler (North-Holland, Amsterdam, 1986) pp. 153–163.

- [103] A. Jávör, Demons in simulation: A novel approach, *Syst. Anal. Mod. Simul.* 7(990)331–338.
- [104] A. Jávör, Intelligent demon controlled simulation of flexible manufacturing system, *Proc. 2nd Beijing Int. Conf. on System Simulation and Scientific Computing* (1992) pp. 333–337.
- [105] J.W. Jones, Applying agricultural models using expert system concepts, *Proc. Amer. Soc. Agricult. Eng.* (1986).
- [106] T.K. Joseph, An expert system advisor to aid goal definition for manufacturing system simulation, *Proc. AI and Simulation*, Simulation Series 20:4 (SCSI, San Diego, CA, 1989) pp. 203–208.
- [107] E.K. Juuso, J.K. Tenteris and K. Leiviskä, Structural models in combined simulation and expert system of ferroalloy processes, *Proc. European Simulation Symp.* (1990) pp. 33–37.
- [108] V. Kachitvichyanakul, S.-W.J. Cheng and D.R. Denzler, KBSIM: A knowledge-based simulator for FMS scheduling and dispatching, *Proc. Summer Computer Simulation Conf.* (1986) pp. 696–698.
- [109] K. Kawamura, Coupling symbolic and numerical computations (Spacecraft control expert system), *IEEE Proc. Int. Conf. on Cybernetics and Society* (1985) pp. 507–510.
- [110] E.J.H. Kerckhoffs, A view on problem-solving paradigms including neurocomputing, *Neural Network World* (Int. J. on Neural and Mass-Parallel Computing and Information Systems, Prague, Czech Republic) 3/91(1991)129–154.
- [111] E.J.H. Kerckhoffs, H. Koppelaar and G.C. Vansteenkiste, Integrating symbolic and neural computing, *Proc. 2nd Beijing Int. Conf. on System Simulation and Scientific Computing* (1992) pp. 1–7.
- [112] E.J.H. Kerckhoffs, G.C. Vansteenkiste and B.P. Zeigler (eds.), *Proc. European Conf. on AI Applied to Simulation*, Simulation Series 18:1 (SCSI, San Diego, CA, 1985).
- [113] L.C. Keskey and D.J. Skyes, An artificial intelligence (AI)-simulation based approach for aircraft maintenance training, *Simulators* Simulation Series 18:4 (SCSI, San Diego, CA, 1987) pp. 285–290.
- [114] A.M. Keuneke, Functional simulation of device: Causal explanation of diagnostic conclusions, *Proc. Summer Computer Simulation Conf.* (1990) pp. 709–714.
- [115] B. Khoshnevis and A-P. Chen, An expert simulation model builder, *Intelligent Simulation Environments*, Simulation Series 17:1 (SCSCI, San Diego, CA, 1986) pp. 129–132.
- [116] B. Khoshnevis and S. Parisay, Machine learning and simulation: Application in queueing systems, *Simulation* 61(1993)294–302.
- [117] M.-H. Kim, III-SE: An Integrated-Interactive-Intelligent Simulation Environment, *Proc. 2nd Beijing Conf. on System Simulation and Scientific Computing* (1992) pp. 95–98.
- [118] T.G. Kim and B.P. Zeigler, ESP-scheme: A realization of system entity structure in a LISP environment, *Proc. AI and Simulation*, Simulation Series 20:4 (SCSI, San Diego, CA, 1989) pp. 135–140.
- [119] J. Kitowski, Simulation of the THTR-steam generator control using artificial intelligence methods, *Proc. IMACS-82*, Vol. 2 (1983) pp. 67–69.
- [120] G.J. Klir, *Aspects of Systems Science* (Plenum, New York, 1991).
- [121] K.J. Kochut, J.A. Miller and W.D. Potter, Design of a CLOS version of active KDL: A knowledge/data base system capable of query driven simulation, *Proc. Artificial Intelligence and Simulation*, Simulation Series 23:4 (SCSI, San Diego, CA, 1991) pp. 139–145.
- [122] R. König and R. Langbein, PROROAD: simulation of the consequences of traffic management strategies on the road traffic, *Proc. European Simulation Multiconf.* (1993) pp. 481–485.
- [123] R.M. Krumholz, CAN BUILD: A state-of-the need inventory simulation tool, in: *Innovative Applications of Artificial Intelligence*, ed. H. Schorr and A. Rappoport (AAAI Press, Menlo Park, CA, 1990) pp. 137–148.
- [124] B. Kuipers, The limits of qualitative simulation, *Proc. 9th Int. Conf. on Artificial Intelligence* (1990) pp. 128–136.
- [125] B. Kuipers, Qualitative simulation, *Art. Int.* 29(1990)289–338.
- [126] N.N. Kwanjai and R.H. Wild, Knowledge-based simulation to assist in system design identification, *Proc. Winter Simulation Conf.* (1992) pp. 822–830.
- [127] C.P. Langlotz, L.M. Fagan, S.W. Tu, J. Williams and B. Sikic, ONYX: An architecture for planning under uncertainty, *Proc. 9th Int. Joint Conf. on Artificial Intelligence* (1985) pp. 447–449.
- [128] G.D. Lanier and B. Vizzier, ESDOTS: An object oriented knowledge based system for space vehicle processing analysis, *Proc. Summer Computer Simulation Conf.* (1991) pp. 380–385.

- [129] A. Lehmann, Knowledge-based modelling and simulation: Restrictions, alternatives and applications, in: *Systems Analysis and Simulation I – Theory and Foundations*, ed. A. Sydow, S.G. Tzafestas and R. Vichnevetsky (Springer, New York, 1988) pp. 412–418.
- [130] B. Li and Q. Zhao, Analogical reasoning as a mechanism for generation of programs, in: *Proc. 2nd Beijing Int. Conf. on System Simulation and Scientific Computing* (1992) pp. 99–104.
- [131] Q. Liang and R.-S. Tu, Intelligent software for simulation of social systems, *Proc. Beijing Int. Conf. on System Simulation and Scientific Computing*, Vol. 1 (1989) pp. 353–356.
- [132] R. Lippmann, An introduction to computing with neural nets, *IEEE ASSP Mag.* (1987) 4–22.
- [133] Y. Lirov, E.Y. Rodin, B.G. McElhany and L.W. Wilbur, Artificial intelligence modelling of control systems, *Simulation* 50(1988)12–24.
- [134] F. Liu and B. Shen, ESSMA – An expert system of simulation model building and algorithm selection, *Proc. 2nd Beijing Int. Conf. on System Simulation and Scientific Computing* (1992) pp. 309–313.
- [135] K.-C. Liu and J.W. Rozenblit, Applying knowledge-based system design and simulation in information system requirements determination, *Proc. Winter Simulation Conf.* (1990) pp. 407–411.
- [136] C. Loehle, Applying artificial intelligence techniques to ecological modelling, *Ecol. Mod.* 38(1987)191–212.
- [137] G.T. Mackulak and J.K. Cochran, MASCOT: A Prolog-based simulation modelling and training environment, in: *Modelling and Simulation Methodology: Knowledge Systems' Paradigms*, ed. M.S. Elzas, T.I. Ören and B.P. Zeigler (North-Holland, Amsterdam, 1987) pp. 145–159.
- [138] C.A. Marsh, RBMS – An expert system for modelling NASA flight control room usage, *Artificial Intelligence and Simulation* (SCSI, San Diego, CA, 1987) pp. 47–50.
- [139] K. Mayoram and D.O. Pederson, Circuit simulation in LISP, *Proc. ICCAD-84* (1987) pp. 24–26.
- [140] M.E. McFall and P. Klahr, Simulation with rules and objects, *Proc. Winter Simulation Conf.* (1986) pp. 470–473.
- [141] J.M. McKinion, Modvex: An expert system for model validation, maintenance, coordination and development, *Proc. 1st AAAI Workshop on Artificial Intelligence and Simulation* (1986) Article No. 8.
- [142] R.R. Meijer and E.J.H. Kerckhoffs, Towards the modelling of knowledge-based control systems in “Duties” (A parallel environment for coupled numeric/symbolic systems), *Proc. European Simulation Symp.* (1990) pp. 73–79.
- [143] J.M. Mellichamp and Y.H. Park, A Statistical expert system for simulation analysis, *Simulation* 50(1989)134–139.
- [144] Y.A. Merkuryev and G.V. Merkuryeva, Expert simulation system for manufacturing processes, *Proc. Summer Computer Simulation Conf.* (1991) pp. 405–408.
- [145] S. Middleton and R. Zanconato, BLOPS: An object-oriented language for simulation and reasoning, in: *AI Applied to Simulation* (1989) pp. 130–135.
- [146] J.G. Moser, Integration of artificial intelligence and simulation in a comprehensive decision support system, *Simulation* 47(1986)223–229.
- [147] H.E. Mueller, L.J. Folse and Brown III, Simulation of animal learning using an inductive memory, *Proc. Artificial Intelligence and Simulation*, Simulation Series 23:4 (SCSI, San Diego, CA, 1991) pp. 104–108.
- [148] R. Muetzelfeld, A. Bundy, M. Uschold and D. Robertson, ECO – An intelligent front end for ecological modelling, in: *AI Applied to Simulation*, Simulation Series 18:1 (SCSI, San Diego, CA, 67–70, 1986) pp. 73–78.
- [149] K.J. Murray, Knowledge-based model construction: An automatic programming approach to simulation modelling, Ph.D. Dissertation, Department. of Computer Science, Texas A&M University, College Station, TX (1986).
- [150] K.J. Murray and S.V. Sheppard, Knowledge-based simulation model specification, *Simulation* 50(1988)112–119.
- [151] G. Nadoli, D. Castillo and J.E. Biegel, HRS: A structure for hierarchical reasoning in knowledge based simulation, *Proc. AI and Simulation*, Simulation Series 22:3 (SCSI, San Diego, CA, 1990) pp. 34–40.

- [152] A. Newell and H.A. Simon, The simulation of human thought, in: *Current Trends in Psychological Theory* (University of Pittsburgh Press, Pittsburgh, 1961) pp. 152–169.
- [153] M.S. Obaidat and D.T. Macchiarolo, On-line neurocomputing system to identify computer users, *Proc. Summer Computer Simulation Conf.* (1992) pp. 403–407.
- [154] R.M. O'Keefe, Advisory systems in simulation, *Proc. AI Applied to Simulation*, Simulation Series 18:1 (SCSI, San Diego, CA, 1986) pp. 73–78.
- [155] R.M. O'Keefe, Simulation and expert systems – A taxonomy and some examples, *Simulation* 46(1986)10–16.
- [156] R.M. O'Keefe, J. Roach and R. Iyengar, Artificial intelligence and simulation, *Proc. 1st AAAI Workshop on Artificial Intelligence and Simulation* (1986) Article No. 21.
- [157] T.I. Ören, Model-based activities: A paradigm shift, in: *Simulation and Model-Based Methodologies: An Integrative view*, ed. T.I. Ören, B.P. Zeigler and M.S. Elzas (Springer, Heidelberg, Germany, 1984) pp. 3–40.
- [158] T.I. Ören, Knowledge bases for an advanced simulation environment, *Proc. Intelligent Simulation Environments*, Simulation Series 17:1 (SCSI, San Diego, CA, 1986) pp. 13–22.
- [159] T.I. Ören, Implications of machine learning in simulation, in: *Modelling and Simulation Methodology in the Artificial Intelligence Era*, ed. M.S. Elzas, T.I. Ören and B.P. Zeigler (North-Holland, Amsterdam, 1986) pp. 41–57.
- [160] T.I. Ören, Quality assurance paradigms for artificial intelligence in modelling and simulation, *Simulation* 48(1987)149–151.
- [161] T.I. Ören, Three simulation experimentation environments: SimAd, SimGest and E/Slam, *Proc. European Simulation Symp.* (1993) pp. 627–632.
- [162] T.I. Ören, D.G. King, L.G. Birta and M. Hitz, Requirements for a repository-based simulation environment, *Proc. Winter Simulation Conf.* (1992).
- [163] T.I. Ören and G. Sheng, Semantic rules and facts for an expert modelling and simulation system, *Proc. 12th IMACS World Congress*, Vol. 2 (1988) pp. 596–598.
- [164] C.M. Oresky, D.B. Lenat, A. Clarkson and S.H. Kaisler, Strategic automatic discovery system (STRADS), in: *Knowledge-Based Simulation: Methodology and Application*, ed. P.A. Fishwick and R.B. Modjeski (Springer, New York, 1991) pp. 223–260.
- [165] C.M. Overstreet and R.E. Nance, World view based discrete event simplification, in: *Modelling and Simulation Methodology in the Artificial Intelligence Era*, ed. M.S. Elzas, T.I. Ören and B.P. Zeigler (North-Holland, Amsterdam, 1986) pp. 165–179.
- [166] M.L. Padgett and T.A. Roppel, Design of a neural network module for integration into a simulation, *Proc. Summer Computer Simulation Conf.* (1992) pp. 390–395.
- [167] Dj.B. Petkovski, Knowledge-based systems for distributed decision making, in: *Systems Analysis and Simulation I – Theory and Foundations*, ed. A. Sydow, S.G. Tzafestas and R. Vichnevetsky (Springer, New York, 1988) pp. 406–411.
- [168] F. Pichler, Model components for symbolic processing by knowledge-based systems: The STIPS framework, in: *Modelling and Simulation Methodology in the Artificial Intelligence Era*, ed. M.S. Elzas, T.I. Ören and B.P. Zeigler (North-Holland, Amsterdam, 1986) pp. 133–143.
- [169] F. Pichler and R.M. Díaz, *Computer Aided Systems Theory – EUROCAST '91* (Springer, Berlin, 1991).
- [170] C.J. Puccia and R. Levins, Qualitative modeling in ecology: Loop analysis, signed digraphs and time averaging, in: *Qualitative Simulation Modeling and Analysis*, ed. P.A. Fishwick and P.A. Luker (Springer, New York, 1991) pp. 119–143.
- [171] A. Radiya and R.G. Sargent, Logic programming and discrete event simulation, *Proc. Simulation and AI* (SCS, San Diego, CA, 1987) pp. 64–71.
- [172] R.K. Ragade, A. Kumar and D.G. Strubel III, Simulation of intelligent operating systems, *Proc. AI and Simulation*, Simulation Series 22:3 (SCSI, San Diego, CA, 1990) pp. 188–193.
- [173] M.T. Rahbar, E. Tanyi, S. Bennett, D.A. Linkens and B. Thomson, An integrated database: Its role in a knowledge-based environment for modelling and simulation (KBMSE), in: *Proc. 3rd European Simulation Congress* (1989) pp. 187–192.

- [174] V.S. Rajput and R.G.S. Asthana, An intelligent visual interactive simulator (IVIS) for planning and analysis of train services, *Proc. European Simulation Symp.* (1990) pp. 203–206.
- [175] M. Rao, J. Tsung-shann, J.J.-p Tsai and C.K. Chang, An intelligent simulation environment for optimal control systems, in: *Proc. Summer Computer Simulation Conf.* (1987) pp. 842–844.
- [176] S.M. Reddy, Knowledge-based techniques for process simulation, *Proc. European Simulation Symp.* (1990) pp. 80–82.
- [177] S.M. Reddy, R. Turton, K.E. Williams, D.B. Godbole and S.M. Potnis, IPSE: A knowledge-based environment for process simulation, *Proc. AI and Simulation*, Simulation Series 20:4 (SCSI, San Diego, CA, 1989) pp. 185–188.
- [178] Y.V.R. Reddy, Epistemology of knowledge-based simulation, *Simulation* 48(1987)162–166.
- [179] Y.V.R. Reddy and M.S. Fox, KBS: An artificial intelligence approach to flexible simulation, Technical Report CMU-RI-TR-81-4, Carnegie Mellon University, Pittsburgh, PA (1980).
- [180] K.D. Reilly and V. Anumolu, Computer simulation of selective neural networks and character handling, *Proc. Summer Computer Simulation Conf.* (1991) pp. 349–351.
- [181] K.D. Reilly, K.W. Ramer, P. Dey, B.W. Suter, H.E. Lyons and J. Byoun, A natural language component for a modeling and simulation environment, in: *Simulation at the Frontiers of Science*, ed. J. Joung, J.W. Ingalls and R. Hawkins (SCSI, San Diego, CA, 1986) pp. 83–88.
- [182] E. Rich and K. Knight, *Artificial Intelligence*, 2nd ed. (McGraw-Hill, New York, 1991).
- [183] J. Rothenberg, Artificial intelligence and simulation, *Proc. Winter Simulation Conf.* (1991) pp. 218–222.
- [184] A. Round, Knowledge-based simulation, in: *The Handbook of Artificial Intelligence*, Vol. 4, ed. A. Barr, P.R. Cohen and E.A. Feigenbaum (Addison-Wesley, Reading, MA, 1989) pp. 415–518.
- [185] M. Rowland, M. Monk and M. Swabey, The simulation of aircrew behaviour for systems integration using knowledge-based programming, *Proc. European Simulation Multiconf.* (1993) pp. 459–463.
- [186] J.W. Rozenblit, J.F. Hu, T.G. Kim and B.P. Zeigler, Knowledge-based design and simulation environment (KBDSE): Foundational concepts and implementation, *J. Oper. Res.* 41(1990)475–489.
- [187] J.W. Rozenblit, S. Sevinç and B.P. Zeigler, Knowledge-based design of LAN's using system entity structure concepts, *Proc. Winter Simulation Conf.* (1986) pp. 858–865.
- [188] J.W. Rozenblit and B.P. Zeigler, Concepts of knowledge based system design environment, *Proc. Winter Simulation Conf.* (1985) pp. 223–231.
- [189] S. Ruiz-Mier, J. Talavage and D. Ben-Arieh, Towards a knowledge-based network simulation environmen, *Proc. Winter Simulation Conf.* (1985) pp. 232–236.
- [190] S. Sakthivel and R. Agarwal, Knowledge-based model construction for simulating information systems, *Simulation* 59(1992)223–236.
- [191] R.R. Salgame, S.G. Becker and D.H. Yu, SPARKS: A knowledge-based process modeling and simulation system, *Proc. Summer Computer Simulation Conf.* (1990) pp. 1147–1156.
- [192] A.J. Santiago and H. Chen, Traffic modeling software for IVHS application, *Proc. Winter Simulation Conf.* (1990) pp. 759–762.
- [193] R.G. Sargent, Exploration of possibilities for expert aids in model validation, in: *Modelling and Simulation Methodology in the Artificial Intelligence Era*, ed. M.S. Elzas, T.I. Ören and B.P. Zeigler (North-Holland, Amsterdam, 1986) pp. 279–297.
- [194] N. Sathi, M. Fox, V. Baskaran and J. Bouer, SIMULATION CRAFT: An artificial intelligence approach to the simulation life cycle, *Proc. Summer Computer Simulation Conf.* (1986) pp. 773–778.
- [195] L.P. Schnepf, A knowledge-based framework supporting the validation process of simulation models, *Proc. European Simulation Symp.* (1992) pp. 39–43.
- [196] L.J. Selig, S. Clearwater, M. Lee and R. Engelsmore, Simulation and expert systems for finding particle beam line errors, *Proc. 2nd AAAI Workshop on AI and Simulation* (1987).
- [197] G. Seliger, B. Viehweger, B. Wieneke-Toutouai and S.R. Kommana, Knowledge-based simulation of flexible manufacturing systems, *Proc. 2nd European Simulation Multiconf.* (1987) pp. 65–68.
- [198] R.E. Shannon, Intelligent simulation environment, *Proc. Intelligent Simulation Environments*, Simulation Series 17:1 (SCSI, San Diego, CA, 1986) pp. 150–156.

- [199] R.E. Shannon, Knowledge based simulation techniques for manufacturing, *Int. J. Prod. Res.* 26(1988)953–973.
- [200] R.E. Shannon and M.A. Centeno, Expert simulation system based on a relational database, *Proc. Winter Simulation Conf.* (1990) pp. 412–414.
- [201] R.E. Shannon, R. Mayer and H.H. Adelsberger, Expert systems and simulation, *Simulation* 44(1985)275–284.
- [202] G. Sheng and T.I. Ören, Computer-aided software understanding systems to enhance confidence of scientific codes, *Proc. BIOMOVs (BIOSpheric Model Validation Study) Symp.* (1991) pp. 275–286.
- [203] H.E. Shrobe, Understanding linkages, *Papers from the AAAI Fall Symp.* (1992) pp. 73–78.
- [204] H.A. Simon, A. Newell, M.L. Minsky, G.A. Miller and S.S. Alexander, Simulation of human thinking, in: *Computers and the World of the Future*, ed. M. Greenberger (MIT Press, Cambridge, MA, 1962) pp. 94–131.
- [205] N. Singh, MARS: A multiple abstraction rule-based simulator, Memo HPP-83-43, Stanford Heuristic Programming Project, Stanford University (1983).
- [206] H.R. Smith and K. McVicar, Knowledge-based simulation with frameworks, *Proc. Artificial Intelligence and Simulation: The Diversity of Applications* (1988) pp. 72–77.
- [207] L. Sokol, S. Geyer, R. Lasken and K. Murphy, ISLE – intelligent scalable logistics environment, *Proc. Winter Simulation Conf.* (1992) pp. 816–821.
- [208] S. Soubra, R. Pelletret and W. Keilholz, Intelligent simulation environments: A first application to building construction. *Proc. European Simulation Multiconf.* (1993) pp. 222–226.
- [209] M. Stelzner, J. Dynis and F. Cummins, The SIMKIT™ system: Knowledge-based simulation and modeling tools in KEE®, *Proc. Winter Simulation Conf.* (1989) pp. 232–234.
- [210] Q.-Z. Sun, C.N. Chrystall and M.M. Kaye, Knowledge-based interactive real-time control system in discrete manufacturing, *Proc. Artificial Intelligence and Simulation*, Simulation Series 23:4 (SCSI, San Diego, CA, 1991) pp. 9–14.
- [211] Q.-Z. Sun, M.M. Kaye and C.N. Chrystall, The role of simulation in the development of an intelligent process control system, AI and simulation, *Proc. AI and Simulation*, Simulation Series 22:3 (SCSI, San Diego, CA, 1990) pp. 153–158.
- [212] J. Synder and G.T. Mackulack, Intelligent simulation environments: Identification of the basics, *Proc. Winter Simulation Conf.* (1988) pp. 357–363.
- [213] E. Tanyi and D.A. Linkens, A frame-based modelling and simulation environment, *Proc. UKSC Conf. on Computer Simulation* (1987) pp. 1215–1219.
- [214] W.M. Tao and X.R. Wang, ICAT: The design and implementation of intelligent control air combat target, *Proc. 2nd Beijing Int. Conf. on System Simulation and Scientific Computing*, (1992) pp. 299–303.
- [215] R.P. Taylor and R.D. Hurrión, An expert advisor for simulation experimental design and analysis. *Proc. Artificial Intelligence and Simulation: The Diversity of Applications* (1988) pp. 238–244.
- [216] S. Thangavadivelu and T.S. Colvin, Decision support system for crop production operations scheduling, *Proc. AI and Simulation*, Simulation Series 20:4 (SCSI, San Diego, CA, 1989) pp. 85–90.
- [217] J.U. Thoma, Bondgraphs for qualitative and quantitative systems modeling, in: *Qualitative Simulation Modeling and Analysis*, ed. P.A. Fishwick and P.A. Luker (Springer, New York, 1991) pp. 217–239.
- [218] S. Treu, Designing a "Cognizant Interface" between the user and the simulation software, *Simulation* 51(1988)227–234.
- [219] C. Tsatsoulis, A review of artificial intelligence in simulation, *ACM SIGART Bull.* 2(1991)115–121.
- [220] M. Turega, Neural networks, in: *Concise Encyclopedia of Software Engineering*, ed. D. Morris and B. Tamm (Pergamon Press, Oxford, UK, 1993) pp. 206–209.
- [221] M. Uschold et al., An intelligent front-end for ecological modelling, *Proc. IJCAI* (1985).
- [222] W. van Braam, W. Dassen, P. Brugada and H. Wellens, Supportive interaction between rule-based and self-learning expert systems in biomedical research, *Proc. Summer Computer Simulation Conf.* (1985) pp. 465–469.
- [223] H. Vangheluwe, L. Vermeersch and G.C. Vansteenkiste, Portable continuous simulation program generators, a tool for intelligent process control, *Proc. European Simulation Symp.* (1990) pp. 66–72.

- [224] G.C. Vansteenkiste, E.H.M. Kerckhoffs and F. Broeckx, Intelligent process control and scheduling and discrete event systems. *Proc. European Simulation Symp.* (1990).
- [225] G.C. Vansteenkiste and E.J.H. Kerckhoffs, DESiRE: Dynamic expert systems in real-time environments, *Proc. 2nd Beijing Int. Conf. on System Simulation and Scientific Computing* (1992) pp. 14–19.
- [226] W. Wang and R. Bell, A knowledge-based system structure for the modelling of flexible manufacturing systems, *Trans. Soc. Comp. Simul.* 9(1992)159–173.
- [227] D. Waye, A. Terroux and M. Walters, SIMSMART: Dynamic simulation for automated control and optimization of complex industrial processes, in: *Modelling and Simulation Methodology: Knowledge Systems' Paradigms*, ed. M.S. Elzas, T.I. Ören and B.P. Zeigler (North-Holland, Amsterdam, 1989) pp. 177–188.
- [228] J. Weinroth and G. Madey, The interface between simulation and neurocomputing, *Proc. AI and Simulation, Simulation Series 22:3 (SCSI, San Diego, CA, 1990)* pp. 1–5.
- [229] R.N. Wendt, Application of program understanding and rule-based quality assurance to Slam II simulation programs, Master's Thesis, Ottawa-Carleton Institute for Computer Science, University of Ottawa, Ottawa, Ont., Canada (1993).
- [230] R.D. Williams (ed), Two approaches to machine intelligence, *IEEE Comp.* 25(1992)78–81.
- [231] B.P. Wise, R.B. Modjeski, Uncertainty management in battle-planning software, in: *Knowledge-Based Simulation: Methodology and Application*, ed. P.A. Fishwick and R.B. Modjeski (Springer, New York, 1991) pp. 261–276.
- [232] R.M. Wnek and S. Springsteen, Application of discrete event simulation techniques to the modeling of asynchronous neural network updating, *Proc. AI and Simulation, Simulation Series 22:3 (SCSI, San Diego, CA, 1990)* pp. 53–58.
- [233] S.-Y. Wu and R.A. Wysk, MPECS – An intelligent flexible machining cell controller, *Proc. European Simulation Multiconf.* (1987) pp. 71–76.
- [234] G. Xiong and A. Song, An expert system for dynamic system simulation, *Proc. AI Applied to Simulation, Simulation Series 18:1 (SCSI, San Diego, 1986)* pp. 106–110.
- [235] L. Yizhi and J.W. Wen, The research of knowledge-based simulation environment KBSE-1, *Proc. 2nd Beijing Int. Conf. on System Simulation and Scientific Computing* (1992) pp. 105–109.
- [236] V.V. Yukhimov and A.I. Gamarnik, Simulation models self-organization at the systems parameters estimation, *Proc. 1993 European Simulation Multiconf.* (1993) pp. 371–375.
- [237] W.A. Zajicek, Transforming a discrete-event system into a logic programming formalism, in: *Modelling and Simulation Methodology in the Artificial Intelligence Era*, ed. M.S. Elzas, T.I. Ören, B.P. Zeigler (North-Holland, Amsterdam, 1986) pp. 181–192.
- [238] P.A. Zalevsky, Knowledge-based simulation of manufacturing facilities, *Proc. Artificial Intelligence and Simulation: The Diversity of Applications* (SCSI, San Diego, CA, 1988) pp. 67–71.
- [239] B.P. Zeigler, DEVS-scheme: A Lisp-based environment for hierarchical, modular discrete event models, Technical Report AIS-2, Computer Engineering Lab., Department. of Electrical and Computer Engineering, University. of Arizona, Tucson, AZ (1986).
- [240] B.P. Zeigler, *Object-Oriented Simulation with Hierarchical, Modular Models – Intelligent Agents and Endomorphic Systems* (Academic Press, Boston, MA, 1990).
- [241] B.P. Zeigler, C.-J. Luh and T.-G. Kim, Model base management for multifaceted systems, in: *AI, Simulation and Planning in High Autonomy Systems*, ed. B.P. Zeigler and J.W. Rozenblit (IEEE Computer Society Press, Los Alamos, CA, 1990) pp. 25–31.
- [242] B.P. Zeigler, J.W. Rozenblit and E.R. Christensen, Reducing the validation bottleneck with a knowledge-based distributed simulation environment, *Expert Syst. Appl.* 3(1991)329–342.
- [243] G.-t. Zhang, An expert simulation system (SAD-1) for effectiveness/cost analysis of a surface-to-air defence system, *Proc. 2nd Beijing Int. Conf. on System Simulation and Scientific Computing* (1992) pp. 498–502.
- [244] J.-G. Zhao and B.-L. Li, An expert mathematical modelling system – EMMS, *Proc. Beijing Int. Conf. on System Simulation and Scientific Computing*, vol. 1 (1989) pp. 520–524.
- [245] J.-G. Zhao and B.-L. Li, An expert mathematical modelling system – EMMS, *Proc. Summer Computer Simulation Conf.* (1991) pp. 1066–1071.